Amendment to the claims:

1. (Currently amended) A method of representing features in an input image to classify the input image as face or nonface, said method comprising ~~calculating its 1-D Haar wavelet representation, amplitude projections, and combining said input image with said 1-D Haar representation and said amplitude projections to form a discriminating feature analysis ("DFA") vector representation of said input image~~ forming vectors from normalized amplitude projections along rows and columns of said image, concatenating said vectors to arrive at a result, and subtracting a mean and dividing by a standard deviation to normalize said result, said step of concatenating to form including processing a Haar representation of said input image and said input image itself.

2. (Cancelled).

3. (previously presented) The method of claim 1 wherein a plurality of DFA vectors are formed based upon training images.

4. (Previously presented) The method of claim 3 wherein said DFA vectors from said training images are used to model face and non face classes using a single multivariate probability distribution function (PDF) for each of said face classes.

5. (Original) The method of claim 4 wherein said models are stored and used for later analysis of input images.

6. (Cancelled)

7. (Previously amended) The method of claim 1 further comprising using said DFA vector of said input image to classify the image using a Bayesian classifier.

8-9. (Cancelled).

10. (Currently amended) A method of classifying an input images as being of a first type or of a second type, the method comprising calculating Gaussian PDFs (Probability Density Functions) of image classes of said first type and of said second type using a single multivariate Gaussian PDF, and utilizing said Gaussian PDFs in conjunction with at least one input image to classify said input image as either being of said first type or of said second type,

wherein said first type is a face and said second type is a nonface.

wherein the PDFs of the face and nonface classes are calculated only after first calculating a DFA (Discriminating Feature Analysis) vector of each of a plurality of training images wherein said DFA vectors are derived by combining said training images, respective 1-D Haar representations of said training images, and respective amplitude projections of said training images, and wherein said DFA is derived by utilizing the amplitude projections along rows and columns of said images to form a plurality of vectors, normalizing said plurality of vectors, concatenating all of the normalized vectors, and then normalizing the combined vectors.

11. (Previously presented) The method of claim 10 wherein a DFA vector of an input image is calculated and a Bayesian discriminator function is used to process the DFA vector of the input image to classify said input image as either a face or nonface.

12. (Previously amended) The method of claim 11 wherein said PDFs of the face and non face classes are calculated based upon a sample set of at least several hundred FERET images.

13. (Currently amended) A method, comprising:

modeling a face class of images, wherein images outside said face class of images are nonfaces within a nonface class; and

modeling a subset of said nonfaces which lie closest to said face class, wherein said nonfaces in said subset are support nonfaces, and wherein ~~at least two of (i)~~ (1) a 1-D Haar representation; (2) an input image; and (3) amplitude projections are calculated for the images and utilized in said modeling, and wherein said method comprises forming a first set of feature vectors from difference images, normalizing said first set of feature vectors, concatenating said normalized vectors to form a different feature vector, and normalizing said different feature vector. ~~modelling.~~

14. (Previously presented) The method of claim 13 wherein said support nonfaces are closest, among said nonfaces in said nonface class, to a decision surface between said face class and said

nonface class.

15. (Previously presented) The method of claim 13 wherein said modeling said support nonfaces comprises:

modeling support nonfaces as a multivariate normal distribution.

16. (Previously presented) The method of claim 13 further comprising:

estimating a conditional density function of said nonface class using a plurality of principal components, an input image, a mean nonface value, and eigenvalues of said nonface class.

17-27 (Cancelled)

28. (previously presented) The method of claim 1 wherein said 1-D ~~Harr~~ Harr representation comprises a horizontal difference image defined by the equation:

$$I_h(i, j) = I(i+1, j) - I(i, j), \text{ where } \quad 1 \leq i < m, 1 \leq j < n.$$

29. (previously presented) The method of claim 1 wherein said 1-D Haar ~~Harr~~ representation comprises a vertical difference image defined by the equation:

$$I_v(i, j) = I(i, j+1) - I(i, j), \text{ where } \quad 1 \leq i \leq m, 1 \leq j < n.$$

30. (previously presented) The method of claim 1 wherein said amplitude projections comprise horizontal projections defined by the equation:

$$X_r(i) = \sum_{j=1}^{n} I(i, j), \text{ where } \quad 1 \leq i \leq m$$

31. (previously presented) The method of claim 1 wherein said amplitude projections comprise vertical projections defined by the equation:

$$X_c(j) = \sum_{i=1}^{m} I(i, j), \text{ where } \quad 1 \leq j \leq n$$

32. (previously presented) The method of claim 10 wherein each said 1-D Haar ~~Harr~~ representation comprises a horizontal difference image defined by the equation:

$$I_h(i, j) = I(i+1, j) - I(i, j), \text{ where } \quad 1 \le i < m, 1 \le j < n.$$

33. (previously presented) The method of claim 10 wherein each said 1-D Haar ~~Harr~~ representation comprises a vertical difference image defined by the equation:

$$I_v(i, j) = I(i, j+1) - I(i, j), \text{ where } \quad 1 \le i \le m, 1 \le j < n.$$

34. (previously presented) The method of claim 10 wherein said amplitude projections comprise horizontal projections defined by the equation:

$$X_r(i) = \sum_{j=1}^{n} I(i, j), \text{ where } \quad 1 \le i \le m$$

35. (previously presented) The method of claim 10 wherein said amplitude projections comprise vertical projections defined by the equation:

$$X_c(j) = \sum_{i=1}^{m} I(i, j), \text{ where } \quad 1 \le j \le n$$

36. (previously presented) The method of claim 13 wherein said 1-D Haar ~~Harr~~ representation comprises a horizontal difference image defined by the equation:

$$I_h(i, j) = I(i+1, j) - I(i, j), \text{ where } \quad 1 \le i < m, 1 \le j < n.$$

37. (previously presented) The method of claim 13 wherein said 1-D Haar ~~Harr~~ representation comprises a vertical difference image defined by the equation:

$$I_v(i, j) = I(i, j+1) - I(i, j), \text{ where } \quad 1 \le i \le m, 1 \le j < n.$$

38. (previously presented) The method of claim 13 wherein said amplitude projections comprise horizontal projections defined by the equation:

$$X_r(i) = \sum_{j=1}^{n} I(i,j), \text{ where } \quad 1 \le i \le m$$

39. (previously presented) The method of claim 13 wherein said amplitude projections comprise vertical projections defined by the equation:

$$X_c(j) = \sum_{i=1}^{m} I(i,j), \text{ where } \quad 1 \le j \le n$$